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The art of scaling up : a computational account on action selection in basal ganglia

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Abstract. What makes a model 'large scale' ? Is it the number of neurons modeled? Or the number of structures modeled in a network? Most of the higher cognitive processes span across co-ordinated activity in different brain areas. However at the same time, the basic information transfer takes place at a single neuron level, together with multiple other neurons. We explore modeling a neural system involving some areas of cortex, the basal ganglia (BG) and thalamus for the process of decision making, using a large-scale neural engineering framework, Nengo. Early results tend to replicate the known neural activity patterns as found in the previous action selection model [2], besides operating with a larger neuronal populations. The power of converting algorithms to efficiently weighed neural networks in Nengo [10, 1] is exploited in this work. Crucial aspects in a computational model, like parameter tuning and detailed neural implementations, while moving from a simplistic to large-scale model, are studied.

Keywords: neural dynamics, basal ganglia, large scale, nengo, decision making

1 Introduction

Action selection is one of the most vital processes for the survival of an organism. The very importance of the process of action selection (and learning from it) in the survival of an organism, pushes for a need of understanding the process from an evolutionary, biological and physiological point of view.

Brain works by running complex dynamics forming complex connections within itself, specific to each behavioral repertoire. It is at the level of few (or many) neurons that the information transfer takes place, which drives all the processes like perception, memory, decision making, language or any other brain process. Ideally, it is that level of detail one wants to model any sub-system of brain or the whole model of brain itself. We start with considering one of our previous works on a computational study of decision making and its dynamics using a thalamo-cortical BG network [8] inspired by [2] and replicated in [11].

The emphasis is on modeling these functional networks at a large scale, both in terms of neuron populations as well as multiple brain structures. To achieve this, we use a neural engineering framework (NEF) based graphical and scripting tool called *Nengo* [10].

2 Methods

2.1 Task

The task is a probabilistic learning task that is described in [9] and used in [2, 11, 8]. Four target shapes are associated with different reward probabilities (see figure 1). Every time any two of the four possible shapes are presented at two random positions (out of the four cardinal positions - up, right, down and left). By the end of trial period, a choice is made and the reward is given according to the reward probability associated with the chosen shape. In a single independent

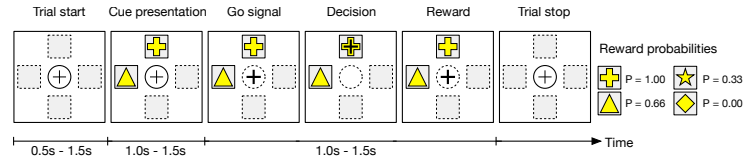


Fig. 1. The two armed bandit task as described in [9, 2].

trial, the cognitive decision (shape of the cue) and motor decision (direction of position) are independent of each other. However, ideally, the motor decision is expected to be in the direction of the cue shape that is chosen. On subsequent reward association of the cue decision, one should eventually select the direction in which the most rewarding cue is present.

2.2 Model

In [4], authors demonstrated an action selection mechanism in the cortico-basal ganglia loops based on a competition between the positive feedback, direct pathway through the striatum and the negative feedback, hyper-direct pathway through the sub-thalamic nucleus. This model allows a bidirectional information flow between loops such that during early trials, a direction can be selected randomly, irrespective of the cue positions. However, after repeated trials, the model is able to consistently make the motor decision, only after cognitive decision, towards the position of the more rewarding cue shape.

2.3 The *NEF* and *Nengo*

The underlying principles of *NEF* are: representation, transformation and dynamics. The activity of a group of neurons is considered to be best represented

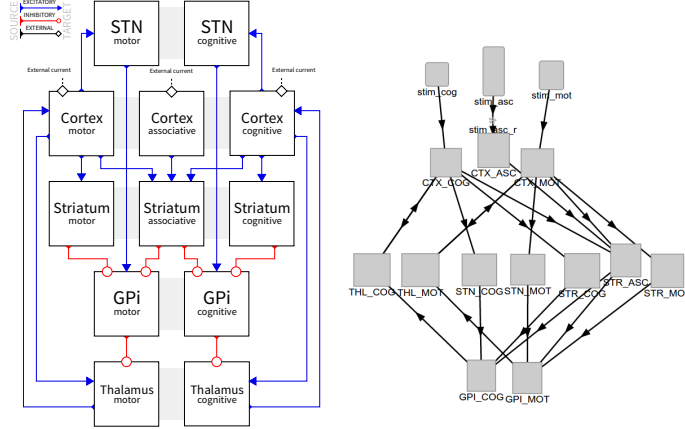


Fig. 2. Architecture of BG model (left) from [2]. A model nengo network (right)

by encoding of some underlying variable, for e.g, any vector generally of smaller dimensionality. The *transformation* of information from one neural group to the other neural group. i.e., the neural group representing \mathbf{x} can be connected to other group of neurons representing a variable \mathbf{y} , such that $\mathbf{y} = f(\mathbf{x})$. Any desired function can be approximated with improved accuracy by increasing the number of neurons. The *dynamics* of NEF allows us to build recurrent neural networks. These networks can compute the time evolution of a given variable \mathbf{x} of the form $\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, \mathbf{u})$.

3 Results

The following simulations assume cue shapes are represented by [0, 1, 2, 3] in the cognitive channel of the cortex and the cardinal directions, where the shapes could be presented, are also represented by [0, 1, 2, 3] in the motor channel of the cortex. The cue shapes have a rewarding probability in the order 1>0>2>3. The synaptic weights that were learned in the previous model were applied. These weights ensure that the highest rewarding cue is always selected. It is also implicit in the model dynamics that the position corresponding to the chosen shape only will be selected. Figure 3 displays the correct cognitive decision (shape) and corresponding motor decision (position).

Model	Cortical level	Total
Simplistic model [2]	24	72
Model implemented	24000	387,200
Full-scale rat model [6]	180K	3 million

Table 1. No. of neurons across models

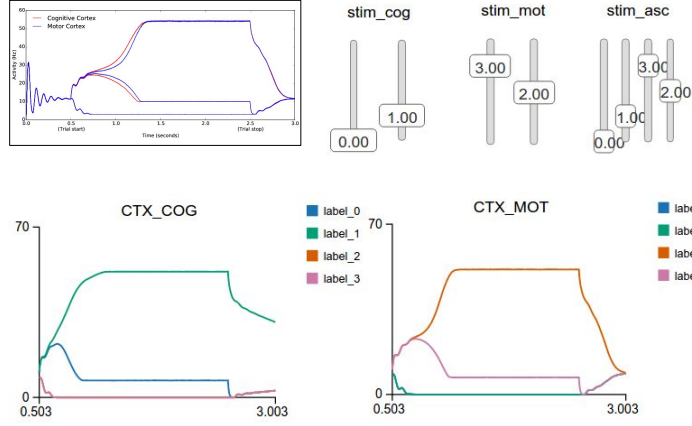


Fig. 3. For the combinations of cue shape and position, the best rewarding cue shape is selected (see CTX_COG) and the corresponding position (as per stim_cog and stim_mot represent shape 0 is shown at position 3 and shape 1 is shown at position 2). It can be seen that, at a point later than choosing shape, corresponding position is chosen (see CTX_MOT). *Inset* The decision in the original simplistic model

4 Discussion

For the models claiming to have network-induced dynamics, the choice of the neuronal dynamics should not make a significant difference. This has been demonstrated clearly in this work. The model developed is tested under similar conditions of action selection task, switching between direct computations and neural implementations like Sigmoidal and Integrate & Fire (IF). To start with, we used simple neurons that directly compute a function. Then the neurons are changed to detailed implementations, but to a lower scale. However, the switch between neuron implementations involved minimal tuning of parameters of the network as well as optimization of few framework parameters, provided there is computational power to handle the large scale of spiking or IF neurons.

Although the population numbers in this work are comparable to that of experimental numbers of a rat's BG and some recent modeling work by Moren et al. 2015 [6] (see table 1), we are still far away from the scale of that of humans' (150K in rats where as 2.2 million neurons, only the globus pallidus and sub-thalamic nucleus combined [3]). As for results, the neural activity corresponding to synaptic weight-driven decision making and the ideal choice as per high reward, were consistent. We also believe, at a full range simulations on the model, performance would match that from the previous simplistic model. In future, such a functional large scale network could become readily usable in other functional processes involving motor reaching or motor learning [5], modeling deficits in neuro-degenerative disorders such as Parkinsonianism [7] etc.

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